DEBLOCKING ALGORITHM FOR DCT-BASED COMPRESSED IMAGES USING ANISOTROPIC DIFFUSION

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ABSTRACT

Among many image compression approaches, the discrete cosine transform(DCT) is widely used. However, dividing an image into small blocks prior to coding causes "blocking artifacts". In this paper, deblocking algorithm for DCT-based compressed images using anisotropic diffusion, derived from ALM diffusion model is proposed. It can control the diffusion rate in the normal direction of the edges using "rate control parameter". It functions not only as an isotropic diffusion at block boundaries of smooth regions, but also an anisotropic diffusion that diffuses the image only in the normal direction of the edges at edges or block boundaries of texture regions. The rate control parameters at block boundaries are chosen carefully to reduce discontinuities. To avoid oversmoothing of the texture region, "speed parameter" is employed. The speed parameter makes diffusion process slow at the texture region, while makes it fast at the smooth region.

1. INTRODUCTION

Most of the international standards for image and video compression, such as JPEG, H.261, H.263, and MPEG[1] recommend the use of the block DCT as a main compression technique. According to the JPEG and MPEG recommendations, the DCT is computed over a number of spatially partitioned regions (typically 16×16 or 8×8) called blocks.

Although DCT is the most popular compression approach, its main drawback is what is usually referred to the "blocking artifacts". Dividing an image into small blocks prior to coding it causes discontinuities between adjacent blocks and affects the strong edges in the image. The blocking artifacts in DCT coded images can be categorized into several kinds as follows : stair case noise along the image edges, grid noise in the smooth regions, corner outliers in the corner points of the 8×8 DCT blocks, ringing artifacts near the strong edges, and corruption of edges across block boundaries [2].

To remove the blocking artifacts, several deblocking techniques have been proposed in the literature as postprocessing methods after DCT based compression, depending on the perspective from which the deblocking problem is dealt with. Generally speaking, they are derived from two different viewpoints, i.e., image enhancement by low-pass filtering and image restoration [3].

Image enhancement methods are heuristic in the sense that no objective criterion is optimized. The easiest way is spatial invariant low-pass filtering of the blocky compressed image[4]. This approach reduces the effect of high frequency tendency but the image is blurred and some details are wiped out. Therefore, a number of adaptive spatial filtering techniques [5][6] have been proposed to overcome this. Generally speaking, adaptive filtering techniques use classification and edge detection to categorize pixels into different classes for adaptation. Classification is essential to adaptive filtering techniques which attempt to exploit local statistics of image regions and the sensitivity of human eyes. Then, different spatial filters are used to blocking artifacts according to the label information.

With image restoration approach, one formulates the postprocessing as an image recovery problem. Reconstruction is performed based on the prior knowledge of the distortion model and the observed data at the decoder. Several classical image restoration techniques, including constrained least squares (CLS), projection onto convex sets (POCS), and maximum a posteriori (MAP) restoration have been used to alleviate block artifacts [2][7][8].

Recently various image processing skills are interpreted as *diffusion process*. The concept of viewing the smoothing process as a diffusion process is first introduced in scale-space theory [9]. After the scale-space theory was introduced, many researchers have embarked on finding various anisotropic (or nonlinear) diffusion models to deal with different problems [10][11]. Its advantages are edge localization and the ability to control scale.

In this paper, deblocking algorithm for DCT-based compressed images using anisotropic diffusion is proposed. Novel diffusion equation is derived from ALM(Alvarez, Lions, Morel) diffusion model [11]. The proposed diffusion equation controls the diffusion rate in the normal direction of edges using "rate control parameter". At the block boundaries of smooth regions, it functions as an isotropic diffusion. However, at the edges or the block boundaries of texture regions, it functions as an anisotropic diffusion that diffuses the image only in the normal direction of the edges. Choice of the rate control parameter is done by using local mean of the magnitudes of gradients. Rate control parameters at block boundaries are chosen carefully to reduce the discontinuities. To avoid oversmoothing of the texture region, "speed parameter" is employed. The speed parameter makes diffusion process slow at the texture region, while makes it fast at the smooth region.

2. DEBLOCKING ALGORITHM USING ANISOTROPIC DIFFUSION

The main drawback of isotropic diffusion equation for noise filtering is smoothing of edges. To overcome the problem, Alvarez, Lions and Morel [11] proposed a degenerate diffusion of the fol-

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lowing kind:

$$I_t = \Delta I - \frac{1}{|\nabla I|^2}\nabla^2 I(\nabla I, \nabla I), \tag{1}$$

where ΔI, ∇I, and $\nabla^2 I$ denote the Laplacian, the Gradient, and the Hessian of I, respectively.

They started from the intuitive idea that “edges” are generally piecewise smooth. Therefore, it seems natural to modify the diffusion operator so that it diffuses more in the direction parallel to the edge and less in the perpendicular one. Eq.(1) is the extreme case of this idea, which diffuses only in the direction of the edge: such a diffusion keeps the location and sharpness of the edge exactly, while it smooths the image on both sides of this edge. The first term of eq.(1), the Laplacian, is the same as in scale space theory, and the second term is an “inhibition” of the diffusion in the direction of the gradient. In a quasi “divergence form”, eq.(1) can also be written as

$$I_t = |\nabla I|\mathrm{div}\frac{\nabla I}{|\nabla I|}, \tag{2}$$

and in more literal formulation as

$$I_t = \frac{1}{I_x^2 + I_y^2}(I_y^2 I_{xx} - 2I_x I_y I_{xy} + I_x^2 I_{yy}). \tag{3}$$

2.1. Novel Diffusion Equation for deblocking

To apply eq.(1) to block artifacts reduction effectively, it should be able to remove various kinds of artifacts mentioned in the previous section simultaneously. Therefore, diffusion equation that can diffuse in all direction, only in the direction of the edge or in the intermediate of the two extreme case is necessary. Control of the diffusion rate of the normal direction of the edges can be achieved by scaling up and down the second term of eq.(1):

$$\begin{aligned} I_t &= \Delta I - \frac{\alpha}{|\nabla I|^2}\nabla^2 I(\nabla I, \nabla I) \\ &= |\nabla I|^\alpha \mathrm{div}\frac{\nabla I}{|\nabla I|^\alpha}, \qquad 0 \le \alpha \le 1, \end{aligned} \tag{4}$$

where α is rate control parameter. Eq.(4) functions as an isotropic diffusion equation as α is close to 0, while it functions as a diffusion equation that diffuses in the normal direction of the edges as α is close to 1.

Fig.1 shows diffused images when rate control parameter is $\alpha = 0$, $\alpha = 0.3$, $\alpha = 0.7$ and $\alpha = 1$ respectively. We can see that the image is less diffused in the normal direction when α increases.

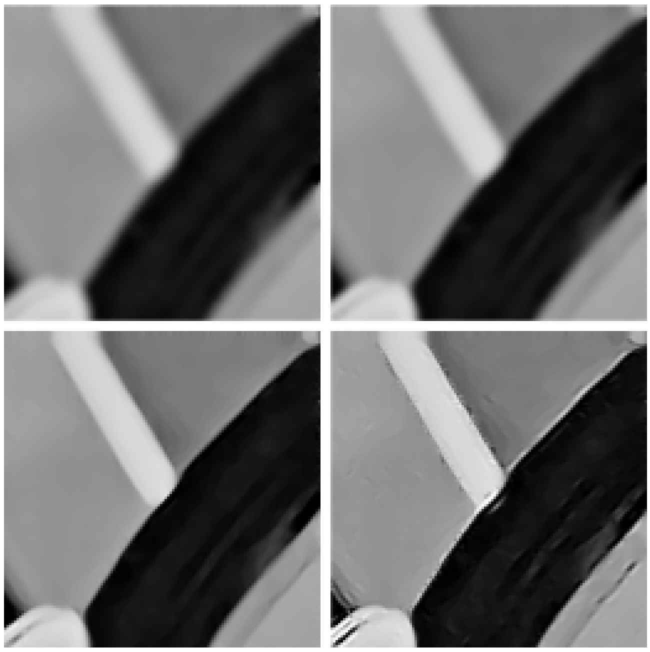


Fig. 1. diffused images when rate control parameter is $\alpha = 0$, $\alpha = 0.3$, $\alpha = 0.7$ and $\alpha = 1$ respectively (after 8 iterations)

2.2. Choice of Rate Control Parameter α

In the previous section, we proposed a novel anisotropic diffusion equation that can control the diffusion rate of the normal direction of the edges. For deblocking, diffusion rate control parameter α should be changed according to the location. Therefore, we make rate control parameter function of $|\nabla I|$. In fact, by letting $|\nabla I|$ be close to “0”, at block boundary and α be constant, block boundary discontinuities can be eliminated. By using adaptive $\alpha(x, y)$, however, we can obtain some advantages. First, we can control the rate of diffusion with ease depending on the strength of edges, preventing the edges from oversharpening or oversmoothing. Second, controlling $|\nabla I|$ with $\alpha(x, y)$ can prevent from oversmoothing at the block boundaries in texture region.

Let $E(x, y)$ be a vector-valued function defined on the image which ideally should have the following properties:

- $E(x, y)$ should be close to 0 at smooth region.
- $E(x, y)$ should be close to 1 at edge region.
- $E(x, y)$ should be close to 0 at the block boundary in smooth region.
- $E(x, y)$ should be close to 1 at the block boundary in texture or edge region.

If $E(x, y)$ is available, the rate control parameter $\alpha(x, y)$ can be chosen to be a function

$$\alpha(x, y) = g(|E(x, y)|). \tag{5}$$

According to the previously stated strategy, $g(\cdot)$ has to be a non-negative monotonically increasing function with $g(\infty) = 1$ (see Fig.2).

Fortunately, because $|\nabla I(x, y)|$ has information whether the position (x, y) is edge or smooth region, $E(x, y)$ can be a function of $|\nabla I(x, y)|$, which we define as

$$E(x, y) = L * |\nabla I(x, y)|_C, \tag{6}$$

where L is a low pass kernel and $|\nabla I(x, y)|_C$ denotes corrected $|\nabla I(x, y)|$ that will be explained below. Since $|\nabla I(x, y)|$ reflects the discontinuities at block boundaries and we want to reduce them, it is reasonable that $|\nabla I(x, y)|$ is corrected with a linearly interpolated value of neighbors. $|\nabla I_{M,N}(i, j)|_C$, the corrected value of the Mth row and Nth column block, is defined as follows:

$$|\nabla I_{M,N}(i, j)|_C = |\nabla I_{M,N}(i, j)|, \quad \text{for} \quad 1 < i, j < 8, \tag{7}$$

$$\begin{aligned} |\nabla I_{M,N}(1, j)|_C &= \tfrac{1}{3}|\nabla I_{M-1,N}(7, j)| + \tfrac{2}{3}|\nabla I_{M,N}(2, j)| \\ |\nabla I_{M,N}(8, j)|_C &= \tfrac{2}{3}|\nabla I_{M,N}(7, j)| + \tfrac{1}{3}|\nabla I_{M+1,N}(2, j)| \end{aligned} \tag{8}$$

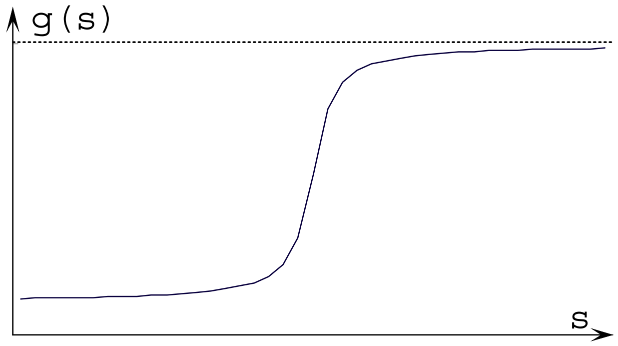


Fig. 2. The qualitative shape of $g(s)$

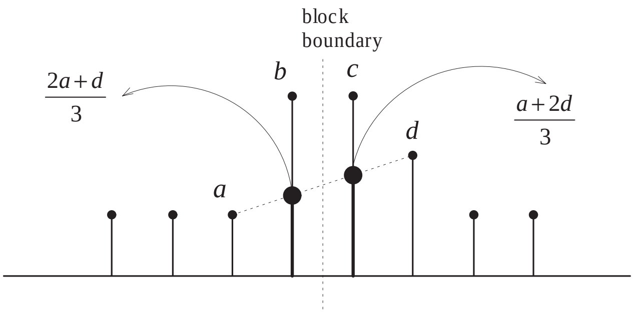


Fig. 3. Linear interpolated value at block boundary

for $1 < j < 8$,

$$\begin{aligned} |\nabla I_{M,N}(i,1)|_C &= \tfrac{1}{3}|\nabla I_{M,N-1}(i,7)| + \tfrac{2}{3}|\nabla I_{M,N}(i,2)| \\ |\nabla I_{M,N}(i,8)|_C &= \tfrac{2}{3}|\nabla I_{M,N}(i,7)| + \tfrac{1}{3}|\nabla I_{M,N+1}(i,2)| \end{aligned} \tag{9}$$

for $1 < i < 8$, and

$$\begin{aligned} |\nabla I_{M,N}(1,1)|_C &= \Big[\big\{\tfrac{2}{3}I_{x(M,N)}(2,1) + \tfrac{1}{3}I_{x(M-1,N)}(7,1)\big\}^2 \\ &\quad + \big\{\tfrac{2}{3}I_{y(M,N)}(1,2) + \tfrac{1}{3}I_{x(M,N-1)}(1,7)\big\}^2\Big]^{1/2} \\ |\nabla I_{M,N}(1,8)|_C &= \Big[\big\{\tfrac{2}{3}I_{x(M,N)}(2,8) + \tfrac{1}{3}I_{x(M-1,N)}(7,8)\big\}^2 \\ &\quad + \big\{\tfrac{2}{3}I_{y(M,N)}(1,7) + \tfrac{1}{3}I_{x(M,N+1)}(1,2)\big\}^2\Big]^{1/2} \\ |\nabla I_{M,N}(8,1)|_C &= \Big[\big\{\tfrac{2}{3}I_{x(M,N)}(7,1) + \tfrac{1}{3}I_{x(M+1,N)}(2,1)\big\}^2 \\ &\quad + \big\{\tfrac{2}{3}I_{y(M,N)}(8,2) + \tfrac{1}{3}I_{x(M,N-1)}(8,7)\big\}^2\Big]^{1/2} \\ |\nabla I_{M,N}(8,8)|_C &= \Big[\big\{\tfrac{2}{3}I_{x(M,N)}(7,8) + \tfrac{1}{3}I_{x(M+1,N)}(2,8)\big\}^2 \\ &\quad + \big\{\tfrac{2}{3}I_{y(M,N)}(8,7) + \tfrac{1}{3}I_{x(M,N+1)}(8,2)\big\}^2\Big]^{1/2} \end{aligned} \tag{10}$$

at the corners of blocks(See Fig.3).

$\alpha(x,y)$ does not matter in eq.(4), since the second term becomes close to 0 in smooth regions. However, in the regions that have ringing artifacts or distorted edges which introduce large oscillation of the gradient, $\alpha(x,y)$ should have small value to reduce and to correct them. This strategy can be satisfied by using the local mean of $|\nabla I(x,y)|_C$. If $|\nabla I(x,y)|_C$ has a small mean value on the neighborhood of a point (x,y), the point (x,y) is considered an interior point of a smooth region of the image and the diffusion is isotropic. If $|\nabla I(x,y)|_C$ has a large mean value on the neighborhood of (x,y), (x,y) is considered an edge point and the diffusion is more anisotropic. Therefore, eq.(6) is reasonable.

To prevent images from oversmoothing and make the algorithm efficitent, we employ ”speed parameter” $s(x,y)$ which has a small value that enables slow diffusion at texture and edge region, and has a large value that enables fast diffusion at smooth region. The following is an example that satisfies such characteristics.

$$s(x,y) = e^{-C\alpha^2(x,y)} \tag{11}$$

By combining the algorithm with the speed parameter $s(x,y)$ we acquire anisotropic diffusion equation for deblocking as follows:

$$I_t(x,y) = s(x,y)|\nabla I(x,y)|^{\alpha(x,y)} \operatorname{div}\left(\frac{\nabla I(x,y)}{|\nabla I(x,y)|^{\alpha(x,y)}}\right). \tag{12}$$

3. EXPERIMENTAL RESULTS

To test the proposed algorithm, four still grayscale images, namely, “lena”, “peppers”, “boats” and “goldhill’, of size 512×512 are used. JPEG recommendation was implemented and quantization table from [8] was used to determine the quantizer in the coder [1]. Compression ratios were 33.9:1, 32.9:1, 27.1:1, 29.6:1 respectively.

As an objective measure of the distance between two images. **g** and **f**, we used the peak signal-to-noise ratio (PSNR). For $N \times N$ images with [0,255] gray level range PSNR is defined in dB by

$$PSNR = 10\log_{10}\left[\frac{N^2 \times 255^2}{\|\mathbf{g} - \mathbf{h}\|^2}\right]. \tag{13}$$

For implementation of the proposed algorithm, eq.(12) can be written as

$$I^{t+1} = I^t + s\left\{I^t_{xx} + I^t_{yy} - \alpha\frac{I^t_{xx}\left(I^t_x\right)^2 + 2I^t_x I^t_y I^t_{xy} + I^t_{yy}\left(I^t_y\right)^2}{\left(I^t_{xx}\right)^2 + \left(I^t_{yy}\right)^2}\right\} \tag{14}$$

In eq.(5), we used $g(s)$ as follows:

$$g(s) = 0.5 + \frac{k_1}{\pi}tan^{-1}\left\{k_2(s - th)\right\} \tag{15}$$

with $k_1 = 0.8$, $k_2 = 10$ and $th = 7$. 5×5 uniform kernel was used for low pass kernel in eq.(6) and $C = 1.44$ was used in eq.(11). The resulting block artifact reduced images after 6 iterations are shown in Fig.4 (b), for “lena” image. As shown in the figure, block boundary discontinuities at smooth regions are removed completely. Artifacts inside the block such as ringing artifacts are also removed effectively. Blurring of texture regions is hardly occurred due to the speed parameter.

We compare the proposed algorithm with two well known conventional deblocking methods in the following. The result of POCS method proposed by Yang *et al.* [8] is shown in Fig.4 (c). As shown in the figure, block artifacts are not removed completely because projection is performed at block boundaries. Pixels inside blocks are affected by quantization constraint set in DCT domain, but its influence is insignificant. Therefore, artifacts inside the blocks are not removed. The result of LPF method proposed by Reeves and Lim [4] is shown in Fig.4 (d). Since low pass kernel is

Algorithm	Image (bpp)			
	Lena (0.295)	Peppers (0.27)	Boats (0.243)	Goldhill (0.236)
JPEG	31.24	30.55	28.40	28.81
POCS	31.52	30.72	28.33	29.03
LPF	32.06	31.14	28.60	29.33
Proposed	32.11	31.66	28.85	29.28

Table 1. PSNR of images processed by various deblocking algorithms

Algorithm	Image (bpp)			
	Lena (0.295)	Peppers (0.27)	Boats (0.243)	Goldhill (0.236)
POCS	0.29	0.17	-0.07	0.23
LPF	0.82	0.59	0.21	0.52
Proposed	0.87	1.11	0.45	0.48

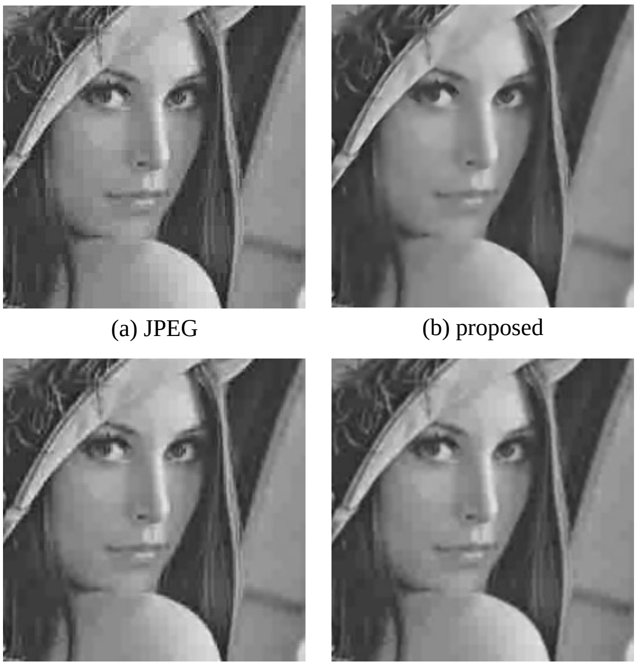
Table 2. Improvements of the PSNR of images processed by various deblocking algorithms

space-invariant, it cannot avoid blurring at the edge region. In addition, block boundary discontinuities are not completely removed because support region of the kernel is restricted.

In Table 1, the PSNR performance of the proposed algorithm is compared with those of conventional algorithms and Table 2 shows the improvements of PSNR. As shown in Table 2, proposed algorithm outperforms the conventional algorithms. Especially, low frequency dominant images(lena, peppers) show remarkable performance.

4. CONCLUSION

In this paper, deblocking algorithm for DCT based compressed images using novel anisotropic diffusion derived from ALM diffusion model was proposed. Proposed diffusion equation can control the diffusion rate in the normal direction of the edges using rate control parameter. To avoid oversmoothing of the texture region, speed parameter was employed. Experimental results indicate that the deblocking algorithm using anisotropic diffusion outperform conventional approaches with respect to both objective and subjective criteria.



(a) JPEG (b) proposed

(c) POCS (d) LPF

Fig. 4. Comparison of the deblocking algorithms

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